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14. ABSTRACT

This management project evaluates factors which may impact Army dental officer retention using logistic regression to develop a discrete-time logit model of dentist retention. This model is intended to aid strategic human resource planning which may also influence future policies regarding the retention of military healthcare professionals. The unit of analysis for this quantitative, exploratory study is all Army dentists on active duty from September 1998 through September 2008. The sample population was 2,003 Active Duty, Army dental officers. The main purpose of this study was to design a useful model for predicting Army dentist retention and factors were identified which were considered significant to this purpose. Additionally, the question of whether or not deployments have affected Army dentist retention since the start of the Global War on Terrorism (GWOT) was also explored.

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An Analysis of Army Dentists Using Logistic Regression:

A Discrete-Time Logit Model for Predicting Retention

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June 10, 2009

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Abstract

This management project evaluates factors which may impact Army dental officer retention using logistic regression to develop a discrete-time logit model of dentist retention. This model is intended to aid strategic human resource planning which may also influence future policies regarding the retention of military healthcare professionals. The unit of analysis for this quantitative, exploratory study is all Army dentists on active duty from September 1998 through September 2008. The sample population was 2,003 Active Duty, Army dental officers. The main purpose of this study was to design a useful model for predicting Army dentist retention and factors were identified which were considered significant to this purpose. Additionally, the question of whether or not deployments have affected Army dentist retention since the start of the Global War on Terrorism (GWOT) was also explored.

Using Minitab® v15, the estimated coefficients, z-values, p-values, and odds ratios were determined for a baseline model and six increasingly complex predictive models. After comparison of goodness-of-fit statistics for the last three models, the model containing demographic factors (Sex, Age, Race, and Family), commissioning sources, dental specialty training, and the intervening effect of GWOT, which was determined by whether the officer was commissioned before or after the start of GWOT, was determined to best fit the data. To achieve greater parsimony, the Sex variable was excluded since there was no significant difference between the model containing Sex and the model excluding Sex. The most significant predictors were determined to be age, racial factors, presence of dependents, commissioning factors, dental specialty, and the effect of GWOT. The recommended model included these significant predictors and a dichotomous response variable representing whether or not an individual exited the Army during the study timeframe.

Contrary to common perceptions, the final results of this study indicate deployments were not significant predictors of retention. Not surprisingly, opportunities for specialty training, having dependents, and entering after October 2001 were found to be significant predictors of retention, which may assist human resource policy makers with developing strategic retention campaigns better focused on those officers more likely to leave.

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Introduction

Conditions that Prompted the Study

The retention of healthcare professionals has long been a challenge to leaders across the military services (Basu, 2005). In particular, the U.S. Army Dental Corps has experienced considerable difficulty recruiting and retaining active duty dental officers throughout the previous decade (McClary, 1999). In an effort to positively affect these personnel issues, coordinated efforts were made in 1996 by the Army, Navy, and Air Force to increase special pays and establish an accession bonus, which were realized in the National Defense Authorization Act for Fiscal Year 1997. However, these incentives provided the most increase in total pay to dental officers with less than three years of service, improving recruiting efforts, but not retention. As McClary (1999) points out, many dental officers were excluded from these benefits, while continued efforts to increase pay to all dental officers were met with little success during the height of military downsizing occurring at the time. Although it is important to emphasize that some degree of turnover is a natural, ongoing process, it is also important to recognize that factors other than pay may impact the matter.

The associated terrorist events of September 11, 2001 (9/11) and America's subsequent invasion of Afghanistan the following month (October 7), mark the start of the Global War on Terrorism (GWOT). Following the initiation of sustained combat operations in support of this war, the Army has found it increasingly difficult to recruit and retain dental officers. This has resulted in critical shortages of available manpower, potentially impacting deployable dental readiness. As the war on terror continues, and dental officers are called on for multiple, increasingly longer deployments, this impact is exacerbated. In order to effectively address retention concerns, it is important to determine those aspects most affecting the situation. These

results may then be used to positively affect dental officer retention policies and procedures in the future.

This management project evaluates factors, other than pay, which may impact Army dental officer retention, then uses the most important factors to develop a predictive model of dental officer retention using discrete time survival analysis techniques. This model may be useful for making strategic human resource decisions and influencing future policies regarding the retention of military healthcare professionals.

Problem Statement

The primary question for this management project is, "What factors impact the retention of Army dentists?" Among these factors, this study is specifically interested in determining the impact of increased deployments by asking "Has GWOT had an impact on the retention of Army dentists?" This question is borne from a general impression among DENCOM leadership that increased frequency and length of deployments have contributed to difficulties retaining Army dentists beyond their initial active duty service obligation (ADSO). To answer this question, this study presents a predictive model of Army dentist retention using variables of interest that are supported by available literature. The key events examined here will be whether and when Army dentists were deployed in support of GWOT. However, other variables that have been found to contribute to employee retention will also be included in the model to enhance its predictive value. GWOT includes all operations conducted directly, or indirectly, in support of the War on Terror, including but not limited to worldwide combat or contingency deployments such as Operation Enduring Freedom (OEF) and Operation Iraqi Freedom (OIF) in the Middle East. Retention is defined as the ability to retain Army dentists on active duty beyond their initial

service obligation. But this is only one aspect of employee turnover, which includes both retention and attrition (personnel losses). For this reason, studies in employee turnover may have merit here, as both fields of interest are inextricably connected (those factors that affect retention have obvious impacts on attrition, and vice versa).

A number of external factors may contribute to this perceived problem. Increased dental practice opportunities in the civilian sector as Baby Boomer dentists enter retirement, in conjunction with other current macroeconomic effects such as rising costs of consumer goods and fuel, a depressed dollar, and the sunken housing market, are among the more prominent possibilities. However, exploration of these possible effects is beyond the scope of this study.

Literature Review and Background

Retention

The retention of Army healthcare professionals has long been of concern to Army leadership. A thorough review of available literature provides the context for this assertion and suggests appropriate variables to examine. A study by McClary (1999) examined factors that influence Army Dental Corps officers' career decisions, specifically the decision to remain in or leave the service. Analysis of the 1997 Dental Officer Recruitment and Retention Survey found these factors to be related to pay, training and education, job satisfaction, quality of life, location, and years of service (McClary, 1999). Specifically, results indicated that officers enrolled in dental specialty programs (hereon referred to as residencies) were more likely to remain in the military beyond their ADSO. Though the effects of financial incentives are not explored in the current study, McClary noted that increases in special pay also influenced dental officers to stay, while low pay influenced them to leave. As these increases were primarily directed at junior

officers still under their initial obligations, it was interesting that he found those with less than six years of service were more likely to leave the service (McClary, 1999). This may have indicated that pay incentives aimed at these junior officers had little impact on their decisions to leave the Army. However, McClary also noted that early opportunities for dental residencies positively affected retention, whereas common demographic factors such as age, sex, rank, marital status, and type of assigned unit did not appear to influence dental officers' intentions (McClary, 1999). It will be interesting to compare the findings of this study with those of McClary's study, which was completed prior to the start of the GWOT.

Further evidence of difficulties in Army dental officer retention were presented in a study by Beer, Chaffin, Mangelsdorff, and Mazuji (2005) who attributed difficulties in the recruitment and retention of junior Army dental officers to a number of external factors. Among the factors addressed were declining dental school enrollment, the presence of a robust economic environment for civilian dentistry, and changing demographic patterns such as the population of Baby Boomer dentists entering retirement. The authors emphasized that recruitment problems over the last decade were addressed with a dental school scholarship known as the Health Professions Scholarship Program (HPSP) as well as accessions bonuses, which are likened to signing bonuses often associated with civilian recruiting practices (Beer et al., 2005). Although these efforts improved recruitment of dental officers between 2002 and 2005, the retention rates for junior dental officers remained low at 43% to 52% over the period (Beer et al., 2005). This further demonstrates how programs designed to bring healthcare professionals, like dentists, into the military should not necessarily be expected to keep them in the service after their initial commitments are fulfilled. Perhaps more importantly, the study illustrates the connection inherent between recruitment and retention, demonstrating some of the external pressures

working against recruiting, and highlighting the effects they also have on retention, luring personnel out as civilian opportunities become more abundant or attractive.

A study by Hsu, Camilla-Tulloch, Roberts, and Trotman (2007) compared recruitment data from before and after September 11, 2001 and found recruitment success for HPSP students was minimally reduced by the impact of war, implying scholarships are appealing to prospective dentists. Though this study is limited in scope to recruitment, comparisons to difficulties in retention may also be drawn. The assertion that recruitment difficulties are at least anecdotally related to retention is premised on the basic assumption that those issues influencing behavior not to join the military quite naturally also influence behaviors to leave. Thus, it would stand to reason that stronger incentives to enter the civilian workforce (such as better pay, increased opportunities to practice dentistry, or simply the stability inherent in a civilian practice), may also serve to draw dental officers out of the military following the end of any obligations incurred from taking advantage of short-term focused recruiting incentives, like the HPSP.

Some literature suggests this may be a valid assumption. According to Basu (2005), financial incentives present in the civilian healthcare sector pose a significant challenge to recruiting physicians and dentists into the military. They further suggest these same incentives also attract military dentists to leave the service after their obligations are fulfilled. As cited in Basu (2005), these observations were illustrated by David Baker, U.S. Army Recruiting Command, who noted that a general dentist can expect to make $173,000 a year coming right out of dental school, whereas specialty dentists and those with more experience can make upwards of $278,000, or over $100,000 more, in the civilian sector (Basu, 2005). Even with special incentive pays, it is difficult for the military to compete with such strong financial enticements to enter civilian practices. Baker emphasized the benefits of leadership and skill development

opportunities as the major selling points that should be promoted by recruiters as they continue to battle the civilian market for America's best and brightest healthcare professionals (Basu, 2005). Recruiting strategies that advertise incentives with longer-term benefits such as these, may also serve to retain these same providers after they have entered service. However, as the author suggests, these benefits may be overshadowed more recently by constant, lengthy deployments of providers in support of the GWOT.

These links become even more apparent against the backdrop of a 1992 survey conducted by George and colleagues, which assessed military physician and dentist attitudes toward deployment following Operations Desert Shield and Desert Storm. The study found the contributing factors for dentists interested in continuing their service as active duty dentists to be: (1) practice opportunities in an active duty environment; (2) positive feelings created by the Desert Storm experience; and (3) possible challenges of practicing in combat (George et al., 1992). They also cited residency opportunities to be among the primary vehicles for attracting healthcare professionals to join the military, recommending recruitment programs continue their emphasis on the challenges and opportunities available to military healthcare professionals (George et al., 1992). Again, the model includes residency opportunities as a predictive factor in retention. A word of caution must be inserted here that comparisons between Desert Storm and current GWOT operations are not implied and will generally be avoided.

Somewhat tangentially related to this study, Austin (2006) identified signs of declines in recruiting quality soldiers as an effect of the continued GWOT. An overall downward trend in quality recruits suggested the possibility of a link between what affects civilian decisions to enter military service and those factors encouraging them to leave. As the current study may show, GWOT may have a profound effect on these decisions.

A RAND study (Fricker, 2002) examined the effects of perstempo on officer retention in the U.S. military betwcen 1990 and 1999 and determined it unlikely that more deployment (increased optempo), or hostile deployment, causes lower retention. The terms "perstempo" and "optempo" are examples of commonly referenced military jargon, which stand for personnel tempo and operations tempo, respectively, and require a short discussion here. Tempo is a musical term meaning the speed at which a musical piece is played, and its meaning has expanded over time to also mean the pace of a given activity. A 1999 Armed Forces Press Service news article by Garamone provides the definition for perstempo, generally accepted service-wide, as a measure of the amount of time an individual spends away from home station (usually denoted in days). Optempo is a measure of the pace of an operation or operations, usually referred to in terms of equipment usage (Garamore, 1999), and more recently expanded to also serve as a measure of the frequency and pace of deploying. The terms are often used interchangeably because their effects are usually seen to rise and fall together (Garamore, 1999). For the purposes of this study, optempo is defined as a measure of the frequency and pace of deploying.

As the number of deployments increased during the timeframe of the 2002 RAND study, the services simultaneously experienced tremendous downsizing across the board. The net effects of these two factors led to significant increases in both perstempo and optempo rates. However, the time period of the RAND study precedes the offensive operations in Iraq and Afghanistan. Further, during that time, the United States was not involved in a sustained war and, with the exception of Operation Desert Storm and a handful of smaller, more limited contingency operations, deployments were largely considered peacetime actions. Today, the U.S. military is approaching its eighth consecutive year of continuous, offensive operations, the last

five years of which have included operations on two fronts. This leads to a reasonable assertion that the context in which the RAND study was conducted, and under which these comments were made, may no longer be relevant given the current environment. Moreover, RAND researchers also suggested that their results may support a hypothesis that unplanned deployments may indeed have a negative impact on retention. Though there is nothing short about an Army GWOT deployment (ranging from 6 to 15 months, with most lasting 12), a case could certainly be made that deployments during the three year period between 2001 to early 2004 were largely unplanned from the perspective of the individual service member.

Discrete-Time Analysis in Retention Studies

The use of discrete-time analysis is uniquely well suited to addressing questions such as "when are active duty Army dentists likely to voluntarily leave the service," and "is the risk of leaving related to a particular experience (like war), or to certain demographic variables (like age or sex)?" These types of questions that ask whether and when events occur and what predicts these occurrences are best addressed by the use of a statistical method known as survival analysis (Keiley & Martin, 2005). According to Keiley and Martin (2005), survival analysis has long been used to model negative occurrences in the medical field, such as time to death from a certain disease. However, questions of whether and when individuals might experience other types of events are equally well suited to methods of survival analysis (Keiley & Martin, 2005). Here, the event of interest is not death, but rather exiting the service. Thus, the time to exit may well be predicted in the same fashion using these techniques to model effects of chosen predictive factors.

But is there a precedent for adapting this approach to the study of retention? Review of the current literature suggests the application of survival analysis in turnover research is not novel. Of note, Morita, Lee, and Mowday (1993) supported the application of survival analysis for turnover studies such as this one. Their presentation focused on life table analysis and the ANOVA (analysis of variance)-analog, while discussing the decisions researchers should make prior to calculating survival equations, interpretation of results, graphical data analysis, and the treatment of time-dependent covariates (Morita et al., 1993). This insight serves as a supporting reference and guide for interpreting the results of this study.

More recently, Mattox and Jinkerson (2005) explored the effects of training on employee retention in a civilian company. They conducted a retrospective, quasi-experimental design to compare the retention of experienced hires attending a three-day training course to the retention of experienced hires who did not attend the training during the same period. Of the three metrics used to assess impact, only two are germane to this study: (1) whether the participants stayed in or left the company and (2) the length of time each study participant remained an employee. The researchers used survival analysis techniques to evaluate the data. Although this study follows a similar experimental design to examine Army dental officer retention, it differs chiefly in the method used to conduct the survival analysis. Mattox and Jinkerson analyzed the means of the two groups with ANOVA and conducted a survival analysis using Cox regression to produce a survival curve. Although Cox regression was better suited to the continuous variables they initially considered using at the beginning of their study, they noted that Kaplan-Meier survival analysis is more useful for determining the impact of categorical variables such as sex or treatment type (Mattox & Jinkerson, 2005).

Another study conducted by Chizmar (2000) provides a further comparison model for studying Army dental officer retention. Chizmar conducted a discrete-time hazard analysis to form a predictive model assessing whether student gender had an effect on the propensity to stay in a particular academic major (referred to as persistence) throughout undergraduate studies. Again, the method and procedures followed in Chizmar's study are well suited for replication with respect to the current research question.

Specifically, this project is modeled after a similar study conducted by Fricker (2002) at the RAND National Defense Research Institute. As discussed earlier, Fricker evaluated the effects of increases in the optempo of the military on officer retention across all services and branches between 1990 and 1999. This study will narrow the focus down to the retention of Army dental corps officers serving on active duty between 1998 and 2008, while assessing the impacts of only hostile deployments, specifically those in support of OIF and OEF. Other variables in Fricker's study are similar to variables in the proposed study (e.g., sex, race, whether or not the officer has dependents, and accession source). As previously mentioned, a deployment variable will be used, denoting whether or not the officer deployed in support of GWOT operations during the period of interest. Other factors that bear on the proposed study include whether and when these officers had the opportunity to complete a residency, allowing for further dental specialization. Additionally, a variable is introduced denoting whether the officer entered the service before or after the start of GWOT. This study examines the survival statistics from a sequential, discrete-time analysis of active duty Army dentists using logistic regression, in order to develop a predictive model of Army dentist retention.

Hypothesis Statements

This study sought to develop a predictive model of Army dental officer retention using a discrete-time logit model, developed through logistic regression. It was hypothesized that an increased optempo of the Army's contemporary operating environment, as evidenced by the length and frequency of GWOT deployments, negatively impacted Army dental officer retention. To that extent, deployment variables were assessed for their contribution to the predictive model. The null hypothesis for model assessment was: H_0 = the data adequately fit the model; the alternate hypothesis was: H_a = the data do not adequately fit the model. A negative effect from deployments would be characterized by a positive coefficient, a p-value $\leq .05$, and inclusion in the best fitting model.

In contrast to the results of the RAND study, negative impacts were expected as frequency and length of deployments increased. The demands on personal responsibilities and constraints on professional goals were believed to be stressed to unacceptable levels with little done to adequately offset the turmoil. Ultimately, these factors, combined with attractive opportunities in the civilian healthcare market, were hypothesized to have a negative impact on dental officer retention.

Method and Procedures

Experimental Design

The unit of analysis for this study is all Army dentists on active duty from September 1998 through September 2008. The aim of this study is to design a useful model for predicting Army dentist retention. As such, this study identifies factors which play a significant role in determining retention. The question of whether or not deployments have affected Army dentist

retention since the start of the GWOT is also explored. These statistics are quantitative in nature, analyzed using Minitab® Statistical Software version 15.

Logistic Regression Statistical Analysis

Multiple logistic regression is ideally suited for use in developing predictive models from large datasets having several variables, when the response variable is dichotomous. Unlike ordinary least squares regression, logistic regression does not assume normality of the data, linearity of the relationship between the independent and dependent variables, or homoscedasticity. In general, logistic regression is not constrained by such considerations or requirements. Originally applied to survival data in the health sciences fields (Berenson, Levine, and Krehbiel, 2004), logistic regression models may be used to predict the probability of a particular categorical response variable (Y), or dependent variable, DV, (such as still serving on AD or exited service) for a given set of explanatory variables (X_i). These explanatory variables may be categorical, time invariant, continuous, or any combination thereof. In this manner, the logistic regression model estimates the odds, or the probability of success compared to probability of failure for the event of interest. This is mathematically expressed below.

$$\text{Odds} = \frac{\text{Probability of event}}{(1 - \text{Probability of event})}$$

The logistic regression equation models the natural logarithm of the odds (logit) that the event of interest occurs, given the predictors. Thus, the generalized logistic regression model for k independent variables is defined as,

$$\ln(\text{odds}) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_k X_{ki} + \varepsilon_i$$

where k = number of independent variables in the model, and ε_i = random error in observation i (Berenson, Levine, and Krehbiel, 2004). Maximum likelihood estimation yields a regression equation capable of predicting the natural log of the odds, defined by the following logistic regression equation estimated from sample data.

$$\ln(\text{estimated odds}) = b_0 + b_1X_{1i} + b_2X_{2i} + \ldots + b_kX_{ki}$$

Upon fitting the logistic regression model to a dataset, the estimated odds ratio is obtained by exponentiating the regression coefficients (estimated odds ratio = e^{bk} ; Berenson, Levine, and Krehbiel, 2004). Summarily, a logistic regression model may be used to predict the estimated probability that an event will occur, given a set of independent variables.

Once a predictive model has been developed, consideration should be given to whether it is a good-fitting model and whether each of the independent variables makes a significant contribution to the model. A commonly used method for determining goodness-of-fit, and which will be used in this study, is the deviance statistic, which follows a chi-square (χ^2) distribution with $n - k - 1$ degrees of freedom (DF). The Wald Statistic, the ratio of the regression coefficient to the standard error of the regression coefficient, will be used in evaluating whether each of the independent variables makes a significant contribution to the model in the presence of the other variables (Berenson, Levine, and Krehbiel, 2004). In this study, the best logistic regression model will be determined through sequential logistic regression model building.

While logistic regression is related to other more common statistical analyses such as discriminant function analysis and multiple regression analysis with a dichotomous DV, answering some of the same or similar questions, logistic regression is far more flexible than other techniques (Tabachnick and Fidell, 2001). Logistic regression requires no assumptions about the distributions of the predictor variables; there is no requirement for the predictors to be

normally distributed, linearly related, of equal variance within each group, or discrete (Tabachnick and Fidell, 2001). In fact, predictors can be any mix of continuous, discrete, and dichotomous variables, making it particularly useful for this type of study. Thus, there were no specific tests required to determine whether the data were appropriate for analysis using logistic regression.

Variables

As discussed previously in the literature review, available research suggests a number of different variables that may impact employee and, even more specifically, military officer retention. The variables included in this study are age, sex, race, family, accession source, residency completion, and deployment. Additionally, an intervention variable is introduced, representing whether or not an individual entered active duty before or after the start of GWOT. These variables are defined in accordance with published data dictionaries from the Defense Manpower Data Center (DMDC) and are meant to be valid for the purposes of this study alone. Table 1 displays variables utilized in logistic regression model building and subsequent analysis. While the variables chosen to predict Army dentist retention included some common demographic information such as age, sex, race, and family, other variables were also included to assess their individual contribution to predicting retention. Those variables with the most significant impact on retention were used to develop the final model.

Table 1.

Variable Code Sheet

Equation Coefficient	Minitab Variable Code	Label	Description	Operationalized	Variable Type	Data Source
Y	Event	Dependent variable	Event of interest; exited service or retained	0 = Still on AD 1 = Left the service	Dichotomous, time variant	DMDC
X_1	Age	Age	Individual's age in years	1, 2, 3, 4,…*n*	Continuous, time variant	DMDC
X_2	Sex	Sex	Female or male	0 = Female 1 = Male	Dichotomous, time invariant	DMDC
X_3	W_R	White race	Caucasian	0 = Non-Caucasian 1 = Caucasian	Dichotomous, time invariant	DMDC
X_4	AA_R	African American race	African American	0 = Non-African American 1 = African American	Dichotomous, time invariant	DMDC
X_5	Family	Eligible Dependents	Had dependents during the study	0 = Did not have dependents 1 = Had dependents	Dichotomous, time invariant	DMDC
X_6	Academy	Military Academy	Military academy graduate	0 = Not academy grad 1 = Academy graduate	Dichotomous, time invariant	DMDC
X_7	ROTC	Reserve Officer Training Corps	ROTC graduate	0 = Not ROTC grad 1 = ROTC graduate	Dichotomous, time invariant	DMDC
X_8	Other_Source	Other Accession	Source of commission is not military academy, ROTC or direct commission	0 = Not Other Accession 1 = Other Accession	Dichotomous, time invariant	DMDC
X_9	AOC	Area of Concentration	Dental specialty assigned	0 = Non-63A 1 = 63A	Dichotomous, time variant	DMDC
X_{10}	GWOT_Intervention	Global War on Terrorism	Whether officer assessed to AD pre- or post-GWOT	0 = Pre-GWOT 1 = Post-GWOT	Dichotomous, time invariant	DMDC
X_{11}	Deployed	Deployed	Did or did not deploy to GWOT during the study	0 = Did not deploy 1 = Deployed	Dichotomous, time invariant	DMDC
X_{12}	Depday	Days Deployed	# of days deployed	1, 2, 3, 4,…*n*	Continuous, time variant	DMDC
$X_{13\text{-}22}$	Period *x*	Period *x*	Indicator of time period (Period 1 = 1998, Period 2 = 1999…Period 10 = 2007)	0 = Any other period 1 = Time period of interest, where *x* = 1, 2, 3…10	Dichotomous, time variant	DMDC

Age is a continuous variable indicating the chronological age of the individual. Sex is a time invariant, dichotomous variable representing the classification of a person based on biological, reproductive function. Race is a time invariant, nominal variable representing the racial group and cultural background with which a person identifies (a nonscientific division of the population based on assumed biological properties). Here, several classifications from the DMDC were combined to create three separate variables: white (Caucasian), black (African American), and other (neither white nor black). Accession source is a time invariant, nominal variable representing how a person was brought into the military on active duty. Again, several classifications were combined to create four separate categories: (1) military academy graduate; (2) ROTC graduate; (3) direct commission and (4) other. Deployed is a time invariant, dichotomous variable representing whether an individual deployed in support of the GWOT over the period of study. Depday is a time variant, continuous variable denoting the number of days an individual was deployed. GWOT_Intervention is a time invariant, dichotomous variable denoting whether an individual entered the Army before or after October 2001 (the start of GWOT). This is meant to explore whether entering the Army after GWOT began had an effect on individuals' retention decisions. AOC is a time variant, dichotomous variable representing whether or not a person completed a dental specialty residency program at some point over the length of the study period. This is evidenced by a change in their AOC at some point in time from 63A, general dentist, to one of nine possible specialization AOCs, accomplished through the completion of a formal residency or fellowship program. Appendix A displays a list of recognized AOCs and their respective specialty.

Sampling

The population for this study includes all active duty Army dentists. The sample of Army dentists for this study includes all dental officers serving on active duty between September 1998 and July 2008 (n = 2,003 individuals). This did not include Reserve or National Guard forces, even those mobilized for active duty. Information on each individual included (1) basic demographical information such as sex, race, and number of dependents; (2) method of accession to active duty service; (3) whether and when the individual completed a dental residency program; and (4) whether and when the individual was deployed in support of GWOT. Table 2 displays descriptive statistics for the sample population. Dentists stay in the Army five years on average, and 23% of the dentists have deployed at some time during the study period.

Initially, the data were collected in three-month snapshots representing discrete time periods over the 10 year timeframe of this study. Beginning with the month of September 1998, information was collected for all individuals serving on active duty at that time, with the process repeating every three months thereafter through July 2008. This starting date was chosen because it represents the earliest date a dentist could have entered AD and be eligible to leave the military by September 2001 immediately before the start of GWOT. The quarterly data were then aggregated to annual data, yielding ten discrete time periods.

This information was then used to create the event of interest, or dependent variable (Event_DV), indicating whether or not an individual exited the service during a specific time period. The starting point for the event of interest is the first recorded time period for which a record exists for an individual during the specified study period. The "event" is whether that individual exited active duty in that time period.

Table 2.

Descriptive statistics for the sample population

Category	Raw	Percentage
Average age during study	39.96	
Average # of years in study	4.94	
Sex		
Males	1717	86%
Females	286	14%
Ethnicity/race		
White/Caucasian	1492	74%
Black/African American	134	7%
Other race category	377	19%
Claimed dependents during study	1664	83%
Completed specialty residency	1162	58%
Accession Source		
Academy graduates	30	1.5%
ROTC graduates	280	14%
Direct Commission	1219	61%
Other accession source	474	24%
Deployed during study	458	23%
Entered AD after Oct 2001	639	32%
Exited service during study (experienced event)	1174	59%

Subjects under study include all U.S. Army dental officers (coded AOC 63-series), as defined by Army Regulation 135-101, with the exception of 63R, Dental Executive, which is awarded by virtue of assigned position rather than dental occupation (Appendix A). As such, these dentists must be a graduate of a dental school accredited by the American Dental Association (ADA) and acceptable to The Surgeon General (TSG), Department of the Army. In

order to practice dentistry in the military, dental officers must possess a Doctor of Dental Surgery (DDS) or Doctor of Dental Medicine (DMD) degree, as well as a valid, current license from one of the fifty United States, a U.S. Territory, or the District of Columbia, and individual credentialing. The individual dentist holding the minimum qualifications previously discussed is granted the AOC classification of 63A, General Dentist, with clinical duties including examination, diagnosis, and treatment of diseases, injuries, and defects of teeth, jaws, oral cavities, and supporting structures. All other recognized dental specialties require additional training in an Advanced Specialty Education Program (commonly referred to as a residency or fellowship) accredited by the ADA and acceptable to TSG, completion of which changes the dentist's AOC. It should be noted that all dental specialists are required to be able to perform the duties of a 63A in addition to their specific AOC. For the purposes of identifying Army dental officers, no distinction is made in this study between 63As and all other specialties. The AOCs of all individuals included in the study were collected only for the purposes of identifying those individuals that completed residencies during the period of interest. This information was used to denote the specific period at which this occurred in the officer's observable career lifespan, and was used as a covariate in the overall discrete-time logit model.

Missing Data

As expected, the dataset included some individuals that had been on active duty already for some time before September 1998 (either with or without some active duty service obligation remaining). In survival analyses, these individuals are referred to as "left censored," since some portion of their observed "lifespan" is outside the parameters of this study. Still other individuals presented the case where they were still serving on active duty during the last possible time

period evaluated for the study (and conceivably beyond), again representing both those with or without service obligations remaining. These individuals are referred to as "right censored." These special circumstances are unique to this type of study, as the researcher is unable to draw accurate conclusions regarding individuals that lie outside the parameters of the study. Since the minimum ADSO for any dental officer accessed to active duty is three years, the minimum number of periods for which complete data are available on any one individual is one, with a maximum of 10 (assuming they were accessed to active duty in September 1998 and exited service in 2008). From these durations, the probabilities of the individuals' experiencing the event can be estimated, as they either "survive" within the military (are retained), or terminate (exit the service; Morita, Lee, & Mowday, 1993).

When the data were collapsed down to one observation per person, it was discovered that there were individuals with many blank fields. It appears as though when the datasets containing accessions and family information were merged with the original person period table, there were extra dentists. This was dealt with by deleting those individuals that were missing Period data.

Regarding the ethnicity/race variables, there were many different categories representing various degrees of ethnic or racial affiliation or identity among the three data dictionaries used to define the dataset. Consequently, the differences in coding from the three data dictionaries presented a burdensome task. To minimize this effect, the respective codes from the dictionaries were merged to create three main ethnic/racial categories: Caucasian/white, African American/black, and Other. The "Other" category handled every other racial category represented by the dictionaries (such as Asian, Pacific Islander, American Indian, etc.). Where an individual was categorized as more than one ethnicity/race, he/she was placed in the "Other" category.

Where there was more than one subcategory for a particular variable (such as Race or Accession Source) interpretation of the odds ratios required the necessary omission of one of the subcategories for comparison purposes. In this manner, the omitted category is the one to which all others are compared. For example, by omitting the Other race subcategory out of the model, the interpretation is that whites (blacks) are more (less) likely than other races to exit the military; if whites were omitted, the comparison would be blacks to whites and others to whites. This study was more interested in whether Caucasians/whites and African Americans/blacks exited the service, rather than some of the smaller groups.

The assumption was made that individual decisions to exit or enter the Army in September 2001 were not affected by the events of 9/11. It is likely these decisions would have been made some time before the month of execution, at least weeks to months in advance. Further, no attempts were made to identify individual officers that may have been affected by stop-loss policies, as this was assumed to be of minimal consequence on the study as a whole.

Procedures

As previously discussed, this is a retrospective, longitudinal study utilizing survival analysis techniques to evaluate Army dentist retention over the timeframe for which GWOT had the possibility of impacting a decision to exit the military following the completion of an initial ADSO. The date of earliest possible ADSO completion for any one individual was September 2001, while the official start of GWOT was the following month, October 2001. Barring stop-loss actions initiated on a case by case basis for deploying combat units, this would be the earliest opportunity an Army dentist would have had to exit the service, avoiding possible combat deployment. There have not been any Army wide stop-loss actions affecting the Dental

Corps collectively at any time during the timeframe of this study. However, individual dentists assigned to combat units at the time of a unit level stop-loss would be retained for the duration of that action, with any allowances for release from active duty approved on a case-by-case basis by individual commanders (in accordance with applicable Army and unit policies and procedures). The limitations of this study preclude making any determinations as to the extent at which this could have impacted the study, and are assumed to be nominal at most.

Advantages to conducting this type of study included minimizing threats to external validity, possibility to make broader generalizations about the population, and efficiency in conducting longitudinal research involving longer periods, which can be followed up later in different environments. The greatest disadvantage is likely the increased threat to internal validity due to the lack of random assignment during data collection, increasing difficulty in determining cause-effect conclusions.

In order to fit this model to data, Singer and Willet (2002) suggest using a person-period data set. This includes all variables of interest, arranged by individual ID and time period. Appendix B depicts an example of the person period table used for this analysis, displaying only 20 variables for the first seven individuals.

Next, a baseline discrete-time logistic regression model was developed, hence forth referred to as Model A:

$$\text{Log (odds)} = [\alpha_1 P_1 + \alpha_2 P_2 + \alpha_3 P_3 + \alpha_4 P_4 + \alpha_5 P_5 + \alpha_6 P_6 + \alpha_7 P_7 + \alpha_8 P_8 + \alpha_9 P_9] + \varepsilon_i$$

The parameter estimates are determined through analysis with appropriate statistical software. Then, successive models are developed, accounting for the effects of substantive predictors in the following equations:

Model B:
$$\text{Logit } h(t_j) = [\alpha_1 P_1 + \alpha_2 P_2 + \ldots + \alpha_9 P_9] + \boldsymbol{\beta_1}(\boldsymbol{Age}) + \boldsymbol{\beta_2}(\boldsymbol{Sex}) + \boldsymbol{\beta_3}(\boldsymbol{W_R}) + \boldsymbol{\beta_4}(\boldsymbol{AA_R}) + \boldsymbol{\beta_5}(\boldsymbol{Family}) + \varepsilon_i$$

Model C:
$$\text{Logit } h(t_j) = [\alpha_1 P_1 + \ldots + \alpha_9 P_9] + [\beta_1(Age) + \ldots + \beta_5(Family)] + \boldsymbol{\beta_6}(\boldsymbol{Academy}) + \boldsymbol{\beta_7}(\boldsymbol{ROTC}) + \boldsymbol{\beta_8}(\boldsymbol{Other\_Source}) + \varepsilon_i$$

Model D:
$$\text{Logit } h(t_j) = [\alpha_1 P_1 + \alpha_2 P_2 + \ldots + \alpha_9 P_9] + [\beta_1(Age) + \ldots + \beta_7(ROTC)] + \boldsymbol{\beta_9}(\boldsymbol{AOC}) + \varepsilon_i$$

Model E:
$$\text{Logit } h(t_j) = [\alpha_1 P_1 + \alpha_2 P_2 + \ldots + \alpha_9 P_9] + [\beta_1(Age) + \ldots + \beta_8(AOC)] + \boldsymbol{\beta_{10}}(\boldsymbol{GWOT\_Intervention}) + \varepsilon_i$$

Model F:
$$\text{Logit } h(t_j) = [\alpha_1 P_1 + \ldots + \alpha_9 P_9] + [\beta_1(Age) + \ldots + \beta_9(GWOT\_Intervention)] + \boldsymbol{\beta_{11}}(\boldsymbol{Deployed}) + \varepsilon_i$$

Model G:
$$\text{Logit } h(t_j) = [\alpha_1 P_1 + \ldots + \alpha_9 P_9] + [\beta_1(Age) + \ldots + \beta_{10}(Deployed)] + \boldsymbol{\beta_{12}}(\boldsymbol{Depday}) + \varepsilon_i$$

Each model introduces one or more new predictor variables. Once all appropriate models have been developed, they are nested and compared using deviance statistics (see Tables 11-12). The strategy for model comparison as explained by Willet and Singer (2002) is found in the manner by which each lower order model is nested within each higher order model, allowing the investigator to directly compare deviance statistics to facilitate analytic decision making.

Logistic Regression Model Building

As with the development of any predictive model, the goal of logistic regression model building is to correctly predict the category of outcome for individual cases using the most parsimonious model available. Table 3 lists the basic steps followed in building a logistic regression model, some of which were alluded to in the preceding section. This sequential approach to model building was utilized to develop the logistic regression model for this study.

Table 3.

Steps Involved In Logistic Regression Model Building

Step	Description
1	Use univariate analysis to identify important covariates (those at least moderately associated with the DV). As a rule, select all variables with $p<0.25$ along with those of known importance.
2	Fit a multiple logistic regression model using the variables previously selected in step 1.
3	Add terms sequentially until further additions do not significantly improve fit.
4	Use the selected model for prediction if appropriate.

Data Quality and Sources

All data for this study were provided by the DMDC, responsible for maintaining the largest archive of personnel, manpower, training, and financial data for the Department of Defense (DoD). Data quality issues presented in this study arise from the fact that all data utilized was gathered second-hand by another agency other than the researcher. The quality of the data gathering and reporting to the DMDC is unknown, but assumed to be sufficiently accurate and comprehensive given their mission and experience in data collection. Further, the data was aggregated from several different databases and systems, including self-reporting methods. Additionally, quality was threatened by the fact that the database utilized by DMDC to store all this information was structurally changed three times over the timeframe of the study, resulting in a need to consult three different data dictionaries to define the information presented in the dataset. This created difficulties where similar variables were defined differently, replaced entirely, or omitted altogether from one system to another.

Data analysis was conducted using Minitab® Statistical Software version 15 to explore the descriptive statistics and conduct the discrete time logistic regression analysis. The initial data collection was followed by thorough data preparation, using Microsoft Office 2003 Excel®. The data was checked for accuracy and appropriately recoded as necessary to make it useful and relevant to the purpose of this study.

Results

In order to form a basis for comparison of the models, the baseline discrete-time logistic regression model was developed as previously explained, including only the DV and first through ninth time periods. Time period 10 was omitted as the referent category.

These variables represented the years an individual was on active duty over the course of the study. In this manner, a value of 1 was recorded for each time period during which the individual was active, with all other periods held at zero. This resulted in one row for every annual period the individual was active during the study, together comprising the person-period table (Appendix B). The results of the baseline logistic regression model are presented in Table 4. For the most part, the odds ratios were largely grouped around 1, except in periods 3 and 4. Period 3 corresponds with the 2000-2001 timeframe and indicated that dentists were 42% less likely to exit the service (odds ratio = .58); period 4 refers to the 2001-2002 timeframe, and indicated dentists were 40% more likely to exit (odds ratio = 1.40) in that period. Interestingly, this two-year span includes the period just before and just after the start of GWOT.

Table 4.

Logistic Regression Model A, baseline with only time periods

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-1.96802	0.0995526	-19.77	0.000			
Period1	-0.342141	0.147848	-2.31	0.021	0.71	0.53	0.95
Period2	-0.0872139	0.140428	-0.62	0.535	0.92	0.70	1.21
Period3	-0.551016	0.157855	-3.49	0.000	0.58	0.42	0.79
Period4	0.336239	0.129095	2.60	0.009	1.40	1.09	1.80
Period5	-0.0262826	0.138925	-0.19	0.850	0.97	0.74	1.28
Period6	0.146729	0.135163	1.09	0.278	1.16	0.89	1.51
Period7	-0.0318237	0.140351	-0.23	0.821	0.97	0.74	1.28
Period8	0.0209242	0.139403	0.15	0.881	1.02	0.78	1.34
Period9	-0.0760781	0.142720	-0.53	0.594	0.93	0.70	1.23

Note: Log-Likelihood = -3580.531; test that all slopes are zero: G = 52.594, DF = 9, P-Value < 0.001. No goodness of fit test performed; the model uses all degrees of freedom; 6 time(s) the standardized Pearson residuals, delta chi-square, delta deviance, delta beta (standardized) and delta beta could not be computed because leverage (Hi) is equal to 1. Regression Equation: Logit $h(t_j) = [\alpha_1 P_1 + \alpha_2 P_2 + \alpha_3 P_3 + \alpha_4 P_4 + \alpha_5 P_5 + \alpha_6 P_6 + \alpha_7 P_7 + \alpha_8 P_8 + \alpha_9 P_9] + \varepsilon_i$

Building on the baseline, the next regression model was fitted with five independent variables, together representing all demographic predictors. The difference in the deviance value between Model A and B, $\chi^2(5) = 30.912$, $p < .05$, was statistically significant. Table 5 displays the estimated coefficients, z-values, p-values, odds ratios, and 95% confidence intervals for the odds ratios for the covariates Age, Sex, Caucasian/White, African American/Black and Family. The estimated coefficients for Age (z = 2.61, p = .009) and Family (z = -5.14, p < .001) have p-values less than .05, indicating there is sufficient evidence that the logit coefficients are not zero. This may be interpreted as dentists with families (spouse, children, or other dependents), being less likely to exit the military than single dentists. Although there is statistical evidence that the estimated coefficient of Age is not zero, the odds ratio is very close to one (1.01), indicating that a one year increase in age minimally affects an individual's retention, and is of little predictive value by itself. However, the p-value (.934) for Sex indicates it was not a significant predictor in this model (p > .05), as was also the case with the ethnicity/race covariates. A more meaningful difference exists with Family (odds ratio = .64), indicating that the odds of an individual leaving

the military decreases by 36% with the addition of dependents. Alternatively, all other factors held constant, the odds of Army dentists in the sample with dependents staying in the military is 56% greater than those without dependents.

Table 5.

Logistic Regression Model B, inclusion of demographic variables

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-2.08290	0.182508	-11.41	0.000			
Period1	-0.369272	0.148865	-2.48	0.013	0.69	0.52	0.93
Period2	-0.121017	0.141376	-0.86	0.392	0.89	0.67	1.17
Period3	-0.583583	0.158653	-3.68	0.000	0.56	0.41	0.76
Period4	0.308462	0.129864	2.38	0.018	1.36	1.06	1.76
Period5	-0.0492770	0.139474	-0.35	0.724	0.95	0.72	1.25
Period6	0.130909	0.135620	0.97	0.334	1.14	0.87	1.49
Period7	-0.0407980	0.140822	-0.29	0.772	0.96	0.73	1.27
Period8	0.0192204	0.139826	0.14	0.891	1.02	0.78	1.34
Period9	-0.0755395	0.143000	-0.53	0.597	0.93	0.70	1.23
Age	0.0094525	0.0036153	2.61	0.009	1.01	1.00	1.02
Sex	-0.0079089	0.0949755	-0.08	0.934	0.99	0.82	1.20
White R	0.168081	0.0948196	1.77	0.076	1.18	0.98	1.42
AA R	0.117123	0.144399	0.81	0.417	1.12	0.85	1.49
Family	-0.451113	0.0878228	-5.14	0.000	0.64	0.54	0.76

Note: Log-Likelihood = -3565.075; test that all slopes are zero: G = 83.506, DF = 14, P-Value < .001. Regression Equation: Logit $h(t_j) = [\alpha_1 P_1 + \alpha_2 P_2 + \ldots + \alpha_9 P_9] + \beta_1(\boldsymbol{Age}) + \beta_2(\boldsymbol{Sex}) + \beta_3(\boldsymbol{W_R}) + \beta_4(\boldsymbol{AA_R}) + \beta_5(\boldsymbol{Family}) + \varepsilon_i$

Next, the accession source variables Academy, ROTC, and Other_Source were added to Model B (see Table 6). The difference in the deviance value between Model B and C, $\chi^2(3) = 25.756$, $p < .05$, was statistically significant. Academy and Other_Source accession were significant predictors ($p < .001$), while participation in an ROTC program was not a statistically significant predictor for exiting the military ($p = .486$). The odds ratios (2.55 and 1.41 for Academy and Other_Source, respectfully) indicate the odds of these individuals staying in the military is 1.41 to 2.55 times that of direct commission dentists. As Other_Source includes such cases as HPSP scholarship recipients, who incur longer ADSOs (like Academy graduates), these individuals will naturally stay in longer, as dictated by their contractual commitments. The

Direct Commission subcategory of accession sources was omitted and used as the basis of comparison.

Table 6.

Logistic Regression Model C, demographic + accession source variables

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	-2.42847	0.210123	-11.56	0.000			
Period1	-0.303714	0.150472	-2.02	0.044	0.74	0.55	0.99
Period2	-0.0525814	0.143102	-0.37	0.713	0.95	0.72	1.26
Period3	-0.538381	0.159523	-3.37	0.001	0.58	0.43	0.80
Period4	0.313030	0.130481	2.40	0.016	1.37	1.06	1.77
Period5	-0.0575448	0.139661	-0.41	0.680	0.94	0.72	1.24
Period6	0.0988996	0.136042	0.73	0.467	1.10	0.85	1.44
Period7	-0.0637652	0.141120	-0.45	0.651	0.94	0.71	1.24
Period8	-0.0070205	0.140172	-0.05	0.960	0.99	0.75	1.31
Period9	-0.0913188	0.143289	-0.64	0.524	0.91	0.69	1.21
Age	0.0158918	0.0040910	3.88	0.000	1.02	1.01	1.02
Sex	-0.0109338	0.0952217	-0.11	0.909	0.99	0.82	1.19
White R	0.166708	0.0951610	1.75	0.080	1.18	0.98	1.42
AA R	0.138766	0.144881	0.96	0.338	1.15	0.86	1.53
Family	-0.468096	0.0884693	-5.29	0.000	0.63	0.53	0.74
Academy	0.937364	0.238428	3.93	0.000	2.55	1.60	4.07
ROTC	0.0635523	0.0911805	0.70	0.486	1.07	0.89	1.27
Other_Source	0.343396	0.0922627	3.72	0.000	1.41	1.18	1.69

Note: Log-Likelihood = -3552.196; test that all slopes are zero: G = 109.262, DF = 17, P-Value < .001. Regression Equation: Logit $h(t_j) = [\alpha_1 P_1 + \alpha_2 P_2 + \ldots + \alpha_9 P_9] + [\beta_1(Age) + \ldots + \beta_5(Family)] + \boldsymbol{\beta_6(Academy)} + \boldsymbol{\beta_7(ROTC)} + \boldsymbol{\beta_8(\text{Other\_Source})} + \varepsilon_i$

Next, the AOC variable was added to Model C (Table 7). The difference in the deviance value between Model C and D, $\chi^2(1) = 161.189$, $p < .05$, was statistically significant. The negative coefficient suggests that those Army dentists in the sample that completed some type of formal residency training to become a specialist were less likely to leave the military ($z = -12.68$, $p < .001$). The odds ratio (.34) suggests the odds of a specialty dentist leaving the military are 34% of the odds of a general dentist leaving, adding some credence to the results of the 2002 RAND study.

Table 7.

Logistic Regression Model D, demographic + accession source + AOC variables

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	95% CI Upper
Constant	-3.01000	0.210591	-14.29	0.000			
Period1	-0.408915	0.151632	-2.70	0.007	0.66	0.49	0.89
Period2	-0.125673	0.144141	-0.87	0.383	0.88	0.66	1.17
Period3	-0.597266	0.160488	-3.72	0.000	0.55	0.40	0.75
Period4	0.240177	0.131766	1.82	0.068	1.27	0.98	1.65
Period5	-0.116770	0.141032	-0.83	0.408	0.89	0.67	1.17
Period6	0.0894516	0.137776	0.65	0.516	1.09	0.83	1.43
Period7	-0.0640112	0.142587	-0.45	0.653	0.94	0.71	1.24
Period8	-0.0175280	0.141704	-0.12	0.902	0.98	0.74	1.30
Period9	-0.0895655	0.144631	-0.62	0.536	0.91	0.69	1.21
Age	0.0438557	0.0045306	9.68	0.000	1.04	1.04	1.05
Sex	0.0002518	0.0959707	0.00	0.998	1.00	0.83	1.21
White R	0.287519	0.0965258	2.98	0.003	1.33	1.10	1.61
AA R	0.118879	0.146362	0.81	0.417	1.13	0.85	1.50
Family	-0.406546	0.0892090	-4.56	0.000	0.67	0.56	0.79
Academy	0.967384	0.241271	4.01	0.000	2.63	1.64	4.22
ROTC	0.154803	0.0924216	1.67	0.094	1.17	0.97	1.40
Other_Source	0.106955	0.0935860	1.14	0.253	1.11	0.93	1.34
AOC	-1.06636	0.0841285	-12.68	0.000	0.34	0.29	0.41

Note: Log-Likelihood = -3471.602; test that all slopes are zero: G = 270.451, DF = 18, P-Value < .001. Regression Equation: Logit $h(t_j) = [\alpha_1 P_1 + \alpha_2 P_2 + \ldots + \alpha_9 P_9] + [\beta_1(Age) + \ldots + \beta_8(Other\_Source)] + \beta_9(AOC) + \varepsilon_i$

Model E evaluated the addition of the GWOT_Intervention variable (Table 8). The difference in the deviance value between Model D and E, $\chi^2(1) = 37.898$, $p < .05$, was statistically significant. Here, the presence of a negative coefficient ($z = -6.12$, $p < .001$) suggests those dentists accessing to AD after 01 October 2001 were actually less likely to leave the military than those who entered prior to the start of GWOT. The odds ratio (.50) suggests the odds of a post-GWOT dentist leaving the military are 50% of the odds of a pre-GWOT dentist leaving. While this is confounding to the hypothesis that more frequent and prolonged deployments would cause more dentists to exit the military, this may also confirm notions that dentists entering the military after the start of GWOT may have done so for different reasons than those who entered before it began. Whether this is attributed to such things as economic factors or patriotic sentiment cannot be discerned at this time.

Table 8.

Logistic Regression Model E, demographic + accession source + AOC + intervention variables

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-2.33564	0.238535	-9.79	0.000			
Period1	-0.742574	0.160843	-4.62	0.000	0.48	0.35	0.65
Period2	-0.454860	0.153456	-2.96	0.003	0.63	0.47	0.86
Period3	-0.935208	0.169202	-5.53	0.000	0.39	0.28	0.55
Period4	-0.117949	0.143400	-0.82	0.411	0.89	0.67	1.18
Period5	-0.421729	0.149330	-2.82	0.005	0.66	0.49	0.88
Period6	-0.150861	0.142999	-1.05	0.291	0.86	0.65	1.14
Period7	-0.209162	0.144458	-1.45	0.148	0.81	0.61	1.08
Period8	-0.0954236	0.142126	-0.67	0.502	0.91	0.69	1.20
Period9	-0.128275	0.144747	-0.89	0.376	0.88	0.66	1.17
Age	0.0364590	0.0047229	7.72	0.000	1.04	1.03	1.05
Sex	-0.0110055	0.0960885	-0.11	0.909	0.99	0.82	1.19
White R	0.288387	0.0966565	2.98	0.003	1.33	1.10	1.61
AA R	0.0723605	0.146603	0.49	0.622	1.08	0.81	1.43
Family	-0.356771	0.0899170	-3.97	0.000	0.70	0.59	0.83
Academy	0.997572	0.242569	4.11	0.000	2.71	1.69	4.36
ROTC	0.120969	0.0927299	1.30	0.192	1.13	0.94	1.35
Other_Source	0.219504	0.0957742	2.29	0.022	1.25	1.03	1.50
AOC	-1.18565	0.0870853	-13.61	0.000	0.31	0.26	0.36
GWOT_Intervention	-0.693504	0.113393	-6.12	0.000	0.50	0.40	0.62

Note: Log-Likelihood = -3452.653; test that all slopes are zero: G = 308.349, DF = 19, P-Value < .001. Regression Equation: Logit $h(t_j) = [\alpha_1 P_1 + \alpha_2 P_2 + \ldots + \alpha_9 P_9] + [\beta_1(Age) + \ldots + \beta_9(AOC)] + \boldsymbol{\beta_{10}(Intervention)} + \varepsilon_i$

Model F includes the Deployed variable (Table 9). Here, the difference in the deviance value between Model E and F, $\chi^2(1) = 0$, $p < .05$, was not statistically significant. Accordingly, the addition of this variable had little impact on the overall goodness-of-fit over Model E, perhaps even slightly degrading it (see Table 12). Hence, deployment did not appear to be a significant predictor of exiting the military as was originally thought ($z = .01$, $p = .995$). Further, the odds ratio (1.00) indicates no effect on retention whether a dentist deployed in support of GWOT or not. Again, these results appear to support the 2002 Rand study.

Table 9.

Logistic Regression Model F, demographic + accession source + AOC + intervention + deployed variables

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-2.33575	0.239040	-9.77	0.000			
Period1	-0.742455	0.161783	-4.59	0.000	0.48	0.35	0.65
Period2	-0.454743	0.154396	-2.95	0.003	0.63	0.47	0.86
Period3	-0.935090	0.170088	-5.50	0.000	0.39	0.28	0.55
Period4	-0.117842	0.144265	-0.82	0.414	0.89	0.67	1.18
Period5	-0.421693	0.149421	-2.82	0.005	0.66	0.49	0.88
Period6	-0.150865	0.143002	-1.05	0.291	0.86	0.65	1.14
Period7	-0.209136	0.144508	-1.45	0.148	0.81	0.61	1.08
Period8	-0.0953832	0.142248	-0.67	0.503	0.91	0.69	1.20
Period9	-0.128257	0.144770	-0.89	0.376	0.88	0.66	1.17
Age	0.0364590	0.0047229	7.72	0.000	1.04	1.03	1.05
Sex	-0.0110482	0.0962911	-0.11	0.909	0.99	0.82	1.19
Wr	0.288384	0.0966576	2.98	0.003	1.33	1.10	1.61
AAr	0.0723561	0.146604	0.49	0.622	1.08	0.81	1.43
Family	-0.356775	0.0899190	-3.97	0.000	0.70	0.59	0.83
Academy	0.997611	0.242636	4.11	0.000	2.71	1.69	4.36
ROTC	0.120970	0.0927300	1.30	0.192	1.13	0.94	1.35
Other_Source	0.219476	0.0958639	2.29	0.022	1.25	1.03	1.50
AOC	-1.18559	0.0874663	-13.55	0.000	0.31	0.26	0.36
GWOT_Intervention	-0.693533	0.113470	-6.11	0.000	0.50	0.40	0.62
Deployed	0.0007911	0.115612	0.01	0.995	1.00	0.80	1.26

Note: Log-Likelihood = -3452.653; test that all slopes are zero: G = 308.349, DF = 20, P-Value < .000. Regression Equation: Logit $h(t_j) = [\alpha_1 P_1 + \alpha_2 P_2 + \ldots + \alpha_9 P_9] + [\beta_1(\mathit{Age}) + \ldots + \beta_{10}(\mathit{Intervention})] + \beta_{11}(\boldsymbol{\mathit{Deployed}}) + \varepsilon_i$

Model G represents the final model assessed, including all variables of interest (see Table 10). Here, again, the difference in the deviance value between Model F and G, $\chi^2(1) = 1.459$, $p < .05$, was not statistically significant. While the negative coefficient for Deployed might suggest those dentists deploying in support of GWOT at some point during the study were less likely to leave the military than those who did not deploy, neither the Deployed variable ($z = -.96$, $p = .336$) nor the Depday variable (representing the number of days the individual was deployed; $z = 1.22$, $p = .221$) appeared to be statistically significant predictors of retention. Further, the proximity of their odds ratios to one (.83 and 1.00, respectively) continue to suggest the odds of a deploying dentist leaving the military are roughly equivalent to the odds of a non-deploying dentist leaving, if not slightly better (slightly more likely to stay in if deployed).

Table 10.

Logistic Regression Model G, demographic + accession source + AOC + intervention + deployed + depday variables

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-2.32947	0.239079	-9.74	0.000			
Period1	-0.746338	0.161781	-4.61	0.000	0.47	0.35	0.65
Period2	-0.458651	0.154396	-2.97	0.003	0.63	0.47	0.86
Period3	-0.939052	0.170089	-5.52	0.000	0.39	0.28	0.55
Period4	-0.120911	0.144258	-0.84	0.402	0.89	0.67	1.18
Period5	-0.415974	0.149485	-2.78	0.005	0.66	0.49	0.88
Period6	-0.151576	0.143041	-1.06	0.289	0.86	0.65	1.14
Period7	-0.216372	0.144666	-1.50	0.135	0.81	0.61	1.07
Period8	-0.0989725	0.142268	-0.70	0.487	0.91	0.69	1.20
Period9	-0.141739	0.145267	-0.98	0.329	0.87	0.65	1.15
Age	0.0363633	0.0047217	7.70	0.000	1.04	1.03	1.05
Sex	-0.0099078	0.0963056	-0.10	0.918	0.99	0.82	1.20
White R	0.287210	0.0966684	2.97	0.003	1.33	1.10	1.61
AA R	0.0689386	0.146626	0.47	0.638	1.07	0.80	1.43
Family	-0.355116	0.0899449	-3.95	0.000	0.70	0.59	0.84
Academy	0.996980	0.242633	4.11	0.000	2.71	1.68	4.36
ROTC	0.119084	0.0927478	1.28	0.199	1.13	0.94	1.35
Other_Source	0.220316	0.0958757	2.30	0.022	1.25	1.03	1.50
AOC	-1.18420	0.0874789	-13.54	0.000	0.31	0.26	0.36
GWOT_Intervention	-0.699320	0.113607	-6.16	0.000	0.50	0.40	0.62
Deployed	-0.190624	0.198217	-0.96	0.336	0.83	0.56	1.22
Depday	0.0012304	0.0010061	1.22	0.221	1.00	1.00	1.00

Note: Log-Likelihood = -3451.923; test that all slopes are zero: G = 309.808, DF = 21, P-Value < 0.001. Regression Equation = Logit $h(t_j)$ = $[\alpha_1 P_1 + \alpha_2 P_2 + \ldots + \alpha_9 P_9] + [\beta_1(Age) + \ldots + \beta_9(Intervention)] + \boldsymbol{\beta_{11}(Deployed)} + \boldsymbol{\beta_{12}(Depday)} + \varepsilon_i$

Assessment of the Final Fitted Model

Following the estimation of coefficients, it is necessary to assess the appropriateness and usefulness of the models (see Tables 12-15). In logistic regression, this is assessed through goodness-of-fit, or how well the model fits the data. Minitab® provides this information in the analysis output, along with guides to interpretation. The tests performed include Pearson, deviance, Hosmer-Lemeshow, and two Brown tests, general alternative and symmetric alternative. The Minitab® Resources section suggests, as a general rule, that p-values less than the accepted α-level (in this case, $p < .05$) would reject the null hypothesis of an adequate fit. Given these outputs, the last three models (E-G) were assessed to have significantly better

goodness-of-fit results than any of the other models. However, the p-value range of .001 to 1.00 indicates that evidence exists to claim the models may not fit the data adequately. It should be noted that these outlier p-values (.001 to .016) corresponded only to the Pearson test. With the exclusion of the Pearson test, the values range from .047 to 1.00, suggesting adequate fit.

Along with goodness-of-fit, measures of association between observed responses and the predicted probabilities were assessed. The measures of association are displayed as tables of the number, percentage number, and percentage of concordant, discordant, and tied pairs, as well as common rank correlation statistics. According to the Minitab® software resources, the Somer's D, Goodman-Kruskal Gamma, and Kendall's Tau-a tests provide summaries of the tables of concordant and discordant pairs. Broadly likened to the R^2 value used for assessing amount of variance captured by a model in linear regression analysis, these values should lie somewhere between 0 and 1, where larger values indicate better predictive ability of the model. As there were essentially no differences in measures of association between the three models, the measure range of .06 to .31 implies less than desirable predictive ability for any of the three models (though they are still twice as good as models A-D, given the same evaluation criteria).

Table 11.

Logistic Regression Model H, Model E less Sex variable

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Constant	-2.34151	0.232982	-10.05	0.000			
Period1	-0.742882	0.160821	-4.62	0.000	0.48	0.35	0.65
Period2	-0.455029	0.153447	-2.97	0.003	0.63	0.47	0.86
Period3	-0.935212	0.169200	-.53	0.000	0.39	0.28	0.55
Period4	-0.118036	0.143397	-0.82	0.410	0.89	0.67	1.18
Period5	-0.421781	0.149329	-2.82	0.005	0.66	0.49	0.88
Period6	-0.150901	0.143000	-1.06	0.291	0.86	0.65	1.14
Period7	-0.209250	0.144456	-1.45	0.147	0.81	0.61	1.08
Period8	-0.0954320	0.142126	-0.67	0.502	0.91	0.69	1.20
Period9	-0.128280	0.144747	-0.89	0.375	0.88	0.66	1.17
Age	0.0364178	0.0047089	7.73	0.000	1.04	1.03	1.05
WR	0.287618	0.0964193	2.98	0.003	1.33	1.10	1.61
AAR	0.0735488	0.146238	0.50	0.615	1.08	0.81	1.43
AOC	-1.18567	0.0870832	-13.62	0.000	0.31	0.26	0.36
GWOT_Intervention	-0.693239	0.113366	-6.12	0.000	0.50	0.40	0.62
Academy	0.996659	0.242442	4.11	0.000	2.71	1.68	4.36
ROTC	0.120796	0.0927160	1.30	0.193	1.13	0.94	1.35
Other_Source	0.219501	0.0957748	2.29	0.022	1.25	1.03	1.50
Family	-0.358427	0.0887433	-4.04	0.000	0.70	0.59	0.83

Note: Log-Likelihood = -3452.660; test that all slopes are zero: G = 308.335, DF = 18, P-Value < 0.001

In comparison of the last three models Model E appeared to represent the best predictive model given the available dataset and covariates available for analysis (see Table 8). In accordance with the model building process, this was based primarily on parsimony (all else being equal, the most simple model should be chosen). That equated to two less covariates than Model G and little to no difference in goodness-of-fit or measures of association. As will be discussed later, Model E was refined further by excluding the Sex variable, and producing Model H, which is considered to be the best-fitted, most parsimonious of the models developed and evaluated during this study. The regression results for Model H are presented in Table 11.

Table 12.

Goodness-of-Fit Assessments for Model E

Method	Chi-Square	DF	P-value
Pearson	4231.25	3955	0.001
Deviance	3608.69	3955	1.000
Hosmer-Lemeshow	5.22	8	0.734
Brown:			
General Alternative	4.08	2	0.130
Symmetric Alternative	3.94	1	0.047

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	6625983	64.6	Somers' D	0.30
Discordant	3516485	34.3	Goodman-Kruskal Gamma	0.31
Ties	111757	1.1	Kendall's Tau-a	0.06
Total	10254225	100.0		

Note: Log-Likelihood = -3452.653; test that all slopes are zero: G = 308.349, DF = 19, P-Value < .001

Table 13.

Goodness-of-Fit Assessments for Model F

Method	Chi-Square	DF	P-value
Pearson	4508.74	4307	0.016
Deviance	3803.25	4307	1.000
Hosmer-Lemeshow	5.40	8	0.714
Brown:			
General Alternative	4.08	2	0.130
Symmetric Alternative	3.94	1	0.047

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	6627138	64.6	Somers' D	0.30
Discordant	3516598	34.3	Goodman-Kruskal Gamma	0.31
Ties	110489	1.1	Kendall's Tau-a	0.06
Total	10254225	100.0		

Note: Log-Likelihood = -3452.653; test that all slopes are zero: G = 308.349, DF = 20, P-Value < .001

Table 14.

Goodness-of-Fit Assessments for Model G

Method	Chi-Square	DF	P-value
Pearson	4739.77	4520	0.011
Deviance	3959.21	4520	1.000
Hosmer-Lemeshow	6.64	8	0.576
Brown:			
General Alternative	3.79	2	0.150
Symmetric Alternative	3.48	1	0.062

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	6627024	64.6	Somers' D	0.30
Discordant	3516011	34.3	Goodman-Kruskal Gamma	0.31
Ties	111190	1.1	Kendall's Tau-a	0.06
Total	10254225	100.0		

Note: Log-Likelihood = -3451.923; test that all slopes are zero: G = 309.808, DF = 21, P-Value < .001

Table 15.

Goodness-of-Fit Assessments for Model H

Method	Chi-Square	DF	P-value
Pearson	3707.99	3359	0.000
Deviance	3261.56	3359	0.883
Hosmer-Lemeshow	5.70	8	0.680
Brown:			
General Alternative	4.15	2	0.126
Symmetric Alternative	3.99	1	0.046

Measures of Association:
(Between the Response Variable and Predicted Probabilities)

Pairs	Number	Percent	Summary Measures	
Concordant	6625005	64.6	Somers' D	0.30
Discordant	3518128	34.3	Goodman-Kruskal Gamma	0.31
Ties	111092	1.1	Kendall's Tau-a	0.06
Total	10254225	100.0		

Note: Log-Likelihood = -3452.660; test that all slopes are zero: G = 308.335, DF = 18, P-Value < .001

In summary, a sequential logistic regression analysis was performed on the dependent variable as outcome (the event defined as exiting the military) and 18 predictor variables: Periods 1 through 9, Age, W_R, AA_R, Family, Academy, ROTC, Other_Source, AOC, and GWOT_Intervention, using Binary Logistic Regression in Minitab® v15. Table 8 displays the estimated coefficients, z-values, p-values, odds ratios, and 95% confidence intervals for the odds ratios corresponding to Model E. The estimated coefficients for covariates Age ($z = 7.72$, $p < .001$), W_R ($z = 2.98$, $p = .003$), Family ($z = -3.97$, $p < .001$), Academy ($z = 4.11$, $p < .001$), Other_Source ($z = 2.29$, $p = .022$), AOC ($z = -13.61$, $p < .001$), and GWOT_Intervention ($z = -6.12$, $p < .001$) all have p-values less than .05, indicating there is sufficient evidence the coefficients are not zero using an α-level of .05. As such, they were evaluated for statistical significance and retained in the model. The negative coefficients associated with Family, AOC, and GWOT_Intervention indicate an inverse, or positive, relationship with retention. Thus suggesting an AD Army dental officer with dependents, who completed specialty dental training, and entered the service after 01 October 2001, would have a greater probability of staying in the military versus those that do not exhibit those characteristics.

Although the covariates AA_R ($z = .49$, $p = .622$) and ROTC ($z = 1.30$, $p = .192$) were not considered to be significant predictors of retention on their own merit, they could not be excluded from the model because they combine with other variables to form whole categories (Race and Accession Source, respectively) which were significant. Consequently, the overall goodness-of-fit of the model drops significantly with their omission.

Although each model demonstrated overall goodness-of-fit, Model E appeared the most statistically sound. Neither of the two deployment variables, Deployed or Depday, were significant in Model G (.336 and .221 respectively), nor was the Deployed variable by itself

significant (Model F, p = .995). Thus, an overall better model fit is achieved by leaving the deployment variables out altogether (Table 8) rather than including any of them (Tables 9 and 10). In an effort to achieve the greatest parsimony, the variable Sex ($z = -.11$, $p = .909$) was also excluded from the model (Tables 11 and 15), though there is no statistical significance associated with its exclusion. Therefore, the resultant model, Model H, was determined by this study to be the most parsimonious, best fitted predictive model for Army dentist retention.

Discussion and Recommendations

Limitations

Anytime generalizations are made for a population from a given sample and time period, limitations for these characterizations must be thoroughly examined with respect to what the data may or may not reveal. This study dealt with time periods in one-year increments over a ten year span. While this was easier to deal with in terms of raw data points, it left much accuracy to be desired in terms of reflecting relationships between covariates and individual behavior, or effects of certain covariates on one another within the model. Further, large generalizations were made in some covariate groups, such as Race, where several different ethnic/racial subcategories were combined to form only three. Some of this owed to the difficulties of dealing with information defined by three different data dictionaries. Further, previous studies suggested race to have little effect on retention in general, thereby suggesting little value in giving much attention to subdividing race into the numerous smaller ethnic/racial distinctions, aside from the two most common populations. Along this vein, granularity was lost on Family and Deployed as well, by handling them as dichotomous "yes/no" variables rather than examining the effects of family size, family transitions, frequency of deployments, or time between deployments.

As evidenced by the increased emphasis on Army leaders to help slow the hemorrhage of soldiers from active duty, and increase in incentives for all ranks and specialties across the board, it is expected that retention rates would decrease over time since the onset of sustained combat operations in support of GWOT. Some evidence suggests that initial recruiting and retention rates may have rose immediately following the World Trade Center attacks on September 11, 2001, due to a heightened sense of patriotism among Americans, particularly service members. This would likely carry through some two years later to the start of Operation Iraqi Freedom (OIF) as well. However, the increased demand for repeated deployments away from loved ones and into austere environments since OIF II was expected to demonstrate a reversal of this trend. While this study expected to find a difference between the findings of the RAND study concerning the effect of deployments on retention, none was found. This may have been due to the manner in which time was recorded, breaking down deployments into days (rather than months). Also, dentists with multiple deployments were not separated from those with only one, making it impossible to make any conclusions other than those previously discussed.

Future studies should assess the impact of multiple deployments (by comparing single deployment dentists with multiple deployment dentists), or the timing of deployments with other life events. It may also be interesting to assess the types of units dentists have deployed with, such as those supporting combat units versus support units, or those assigned to the deploying unit versus those temporarily filling vacancies through the Army Professional Filler System (PROFIS). As there was some evidence in the literature to suggest a positive effect of leadership experience and training on retention, this should also be explored. While some leadership data was available to this study from the initial dataset, it was incomplete for the sample population, precluding analysis.

Overall, few recommendations may be made from the results of this study. Efforts should be made to sustain or improve opportunities for specialization (such as residencies and fellowships), as well as professional continuing education. While not specifically addressed, future studies may evaluate the impact of professional affiliation as well. There is also definite need to better capture feedback from exiting officers with appropriate survey instruments. This information could be used to validate studies such as this and create more useful predictive models. The significance of the deployment variables chosen for this study was dependent on how the individual variable was defined. As deployment variables chosen for this study were not found to be significant predictors of retention, perhaps there is little reason for concern over the possibility that junior to mid-grade dental officers deploying in support of the GWOT are likely to leave the military due to that factor alone. Thus, no recommendations can be made concerning changes to deployment optempo of Army dental officers.

Finally, this predictive model of dentist retention may be useful to future retention efforts by providing Army leaders with a better idea of where and how to focus retention campaigns. Emphasis should be placed on the benefits of being a commissioned officer in the military service, such as leadership opportunities, teamwork philosophy, and benefits to family life. Additionally, efforts should also be made to highlight opportunities for specialty dental training and increased opportunity to practice dentistry without the concerns of managing a practice, maintaining costly malpractice insurance, and marketing efforts to sustain and grow the patient base. These results may further aid in updating retention policies in the Army Dental Command, and serve as a model for other healthcare specialties throughout other military services facing similar retention challenges.

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Appendix A

Army Dental AOC Classifications

AOC	Classification
63A	General Dentist
63B	Comprehensive Dentist
63D	Periodontist
63E	Endodontist
63F	Prosthodontist
63H	Public Health Dentist
63K	Pediatric Dentist
63M	Orthodontist
63N	Oral and Maxillofacial Surgeon
63P	Oral Pathologist
63R	Executive Dentist

Appendix B

The Person Period Dataset (example displaying only 20 variables for first seven individuals)

ID	Period	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	Age	Sex	W_R	AA_R	O_R	AOC	GWOT_ Intervention	Event	Deployed
000195458	1	1	0	0	0	0	0	0	0	0	0	42	1	1	0	0	1	0	0	0
000195458	2	0	1	0	0	0	0	0	0	0	0	43	1	1	0	0	1	0	0	0
000195458	3	0	0	1	0	0	0	0	0	0	0	44	1	1	0	0	1	0	0	0
000195458	4	0	0	0	1	0	0	0	0	0	0	45	1	1	0	0	1	0	0	0
000195458	5	0	0	0	0	1	0	0	0	0	0	46	1	1	0	0	1	0	0	0
000195458	6	0	0	0	0	0	1	0	0	0	0	47	1	1	0	0	1	0	1	0
000674269	1	1	0	0	0	0	0	0	0	0	0	40	1	1	0	0	0	0	0	1
000674269	2	0	1	0	0	0	0	0	0	0	0	41	1	1	0	0	0	0	1	1
001676702	10	0	0	0	0	0	0	0	0	0	0	28	1	1	0	0	1	1	0	0
001676702	11	0	0	0	0	0	0	0	0	0	1	29	1	1	0	0	1	1	1	0
001826920	7	0	0	0	0	0	0	1	0	0	0	30	1	1	0	0	0	1	0	1
001826920	8	0	0	0	0	0	0	0	1	0	0	31	1	1	0	0	0	1	0	1
001826920	9	0	0	0	0	0	0	0	0	1	0	32	1	1	0	0	0	1	0	1
001826920	10	0	0	0	0	0	0	0	0	0	0	33	1	1	0	0	0	1	1	1
003013661	11	0	0	0	0	0	0	0	0	0	1	29	0	0	0	1	0	1	1	0
003692213	1	1	0	0	0	0	0	0	0	0	0	40	1	0	0	1	0	0	0	0
003692213	2	0	1	0	0	0	0	0	0	0	0	41	1	0	0	1	0	0	0	0
003692213	3	0	0	1	0	0	0	0	0	0	0	42	1	0	0	1	0	0	0	0
003692213	4	0	0	0	1	0	0	0	0	0	0	43	1	0	0	1	0	0	0	0
003692213	5	0	0	0	0	1	0	0	0	0	0	44	0	0	0	1	0	0	0	0
003692213	6	0	0	0	0	0	1	0	0	0	0	45	0	0	0	1	0	0	0	0
003692213	7	0	0	0	0	0	0	1	0	0	0	46	0	0	0	1	0	0	0	0
003692213	8	0	0	0	0	0	0	0	1	0	0	47	0	0	0	1	1	0	0	0
003692213	9	0	0	0	0	0	0	0	0	1	0	48	0	0	0	1	1	0	0	0
003692213	10	0	0	0	0	0	0	0	0	0	0	49	0	0	0	1	1	0	0	0
003692213	11	0	0	0	0	0	0	0	0	0	1	50	0	0	0	1	1	0	1	0
004564287	1	1	0	0	0	0	0	0	0	0	0	30	1	1	0	0	0	0	1	0